TRANSNAV
http://www.transnav.eu
the International Journal on Marine Navigation and Safety of Sea Transportation
Volume 11
Number 3
September 2017
DOI: 10.12716/1001.11.03.18

Validation of Radar Image Tracking Algorithms with Simulated Data

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ABSTRACT: Collision avoidance is one of the high-level safety objectives and requires a complete and reliable description of the maritime traffic situation. The radar is specified by the IMO as the primary sensor for collision avoidance. In this paper we study the performance of multi-target tracking based on radar imagery to refine the maritime traffic situation awareness. In order to achieve this we simulate synthetic radar images and evaluate the tracking performance of different Bayesian multi-target trackers (MTTs), such as particle and JPDA filters. For the simulated tracks, the target state estimates in position, speed and course over ground will be compared to the reference data. The performance of the MTTs will be assessed via the OSPA metric by comparing the estimated multi-object state vector to the reference. This approach allows a fair performance analysis of different tracking algorithms based on radar images for a simulated maritime scenario.

1 INTRODUCTION

The need for an accurate and resilient situational awareness has been increasingly growing in the maritime domain due to a variety of reasons: the ever increasing global trade constantly calls for ships larger in size and numbers, which still need to navigate the international waterways and harbors in a secure and efficient manner. In addition, it is a stringent necessity to traffic management and security authorities to detect abnormal vessel behavior, to prevent harm to marine infrastructure, humans and nature. Apart from that, the trend towards autonomous navigation is clearly entering the maritime world calling for advanced solutions as enabling technologies. From our perspective two conclusions can be drawn from these considerations: firstly, maritime situation awareness is crucial to all of these applications and secondly, the described challenges call for a refined and more reliable situation picture. The dominating source for traffic situation assessment in the maritime domain has been and will be the marine radar, which is still the primary sensor for collision avoidance. Various approaches have been published in the literature to augment maritime surveillance or collision avoidance systems, mostly based on radar fusion with additional sensors such as laser in Perera, Ferrari, Santos, Hinostroza, and Soares (2015) or multiple stationary radar systems for exploiting aspect angle diversity as in Braca, Vespe, Maresca, and Horstmann (2012). The matter of AIS and radar fusion was mainly addressed for anomaly detection, e.g., based on multi hypothesis tests in Guerriero, Willett, Coraluppi, and Carthel (2008) or by exploiting historical traffic route knowledge for SAR/AIS fusion in Mazzarella and Vespe (2015). In Kazimierski and Stateczny (2015) an overview was given for different AIS/radar fusion techniques incorporating online covariance estimation. In Siegert, Banyś, and Heymann (2016) and Siegert, Banyś, Hoth, and Heymann (2017), implementations of IMM-MSPDA and IMM-JPDA filters were applied to on-board maritime traffic situation assessment considering single and multiple targets in a clutter environment, respectively. These approaches all follow the basic assumptions of classical Kalman filtering concerning Gaussian process and measurement noise and that the problem formulation is only mildly nonlinear. In cases, in which these assumptions do not hold, particle filtering has become a popular alternative. Introduced by different authors, such as Gordon, Salmond, and Smith (1993), Kitagawa (1996) and Isard and Blake (1998), a particle filter implements the formal recursive Bayesian filter using sequential Monte Carlo methods. The sought for posterior probability distribution function (pdf) of the state vector is not described in a functional form, but is instead approximated by a set of random samples. The application of particle filters to marine radar images for fusing radar data with AIS was introduced in Heymann, Banyś, and Saez (2015) arguing that the Gaussian noise assumption might be violated when using radar images as measurement input. In this study, we want to compare the performance of both classes of recursive Bayesian filters in a maritime multi-target scenario. For this reason, an Interacting Multiple Model (IMM)-Joint Probabilistic Data Association (JPDA) filter was designed based on Unscented Kalman filtering (UKF) that is conditioned on measurement data from radar images. In fact a blob detector is applied to extract target candidates from one radar image. This filter will be compared against a newly proposed Repulsive Multi Particle Filter (RMPF) that is conditioned directly on the current radar image.

The remainder of this document is organized as follows. The simulated reference scenario will be described in Section 2. This is followed by the proposal of two methods for multi-target tracking based on radar image processing in Section 3. Both frameworks will be evaluated and compared in their performance in Section 4. A conclusion and outlook is given in Section 5.

2 SIMULATION OF MARITIME SCENARIO

For evaluation of both multi-target trackers a maritime scenario was simulated with a commercial ship navigation simulator (ANS6000 by Rheinmetall AG). Two tugs were set up to maneuver in the vicinity of a third ship, which was anchored. The simulated radar response of this quasistatic vessel was used as input to both multi-target trackers. Figure 1 shows the configured tracks, while Figure 2 depicts one radar scan during the simulation time. The multi-target reference data was obtained from interfacing to the NMEA output on the serial port of the simulator, which contained the encoded AIS messages.

3 MULTI-TARGET TRACKERS

In general, the field of multi-target tracking (MTT) in presence of multiple and in general imperfect sensors has been widely explored, ranging from classical enumerative to non-enumerative schemes. Algorithms representing the former category, such as Global Nearest Neighbor (GNN) and Joint Probabilistic Data Association (JPDA) filtering, integer programming or Multi Hypothesis Tracking (MHT) are well-described in Bar-Shalom, Daum, and Huang (2009), Kim, Li, Ciptadi, and Rehg (2015), Pulford (2005) and Khaleghi, Khamis, Karray, and Razavi (2013). More recent work has also applied Random Finite Set (RFS) theory to MTT yielding the Probability Hypothesis Density (PHD) or Cardinalized PHD (CPHD) filters Mahler (2015). In specific situations where the assumption of linear state equation under Gaussian noise is violated, sequential Monte Carlo methods Doucet, Smith, de Freitas, and Gordon (2001) can be considered as an alternative solution Hue, Le Cadre, and Pérez (2002). Thanks to the ever increasing availability of computing power the computational needs, one of the drawbacks of particle filter algorithms, become less constraining for real time applications. In this work, we want to compare the performance of two different multi-target trackers in a maritime scenario in terms of their estimated multi-target state. At first, an IMM-JPDA filter was implemented as current state-of-the-art approach for MTT. Secondly, a novel Repulsive Multi Particle Filter (RMPF) will be introduced which is not subject to the Gaussian error state assumption.

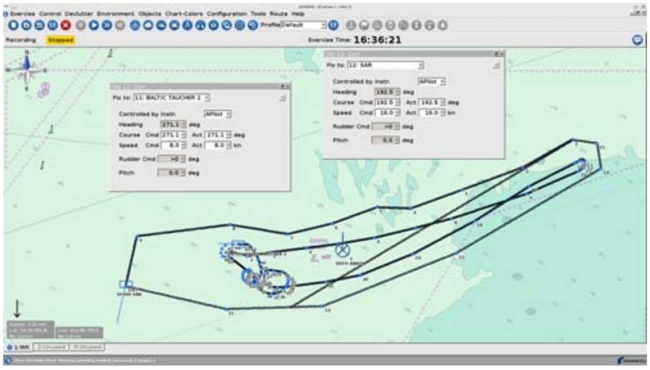


Figure 1. Simulated multi-target scenario in the Baltic Sea. Two tugs were steered to circle around an anchored (quasistatic) vessel, which monitors the situation by her radar.

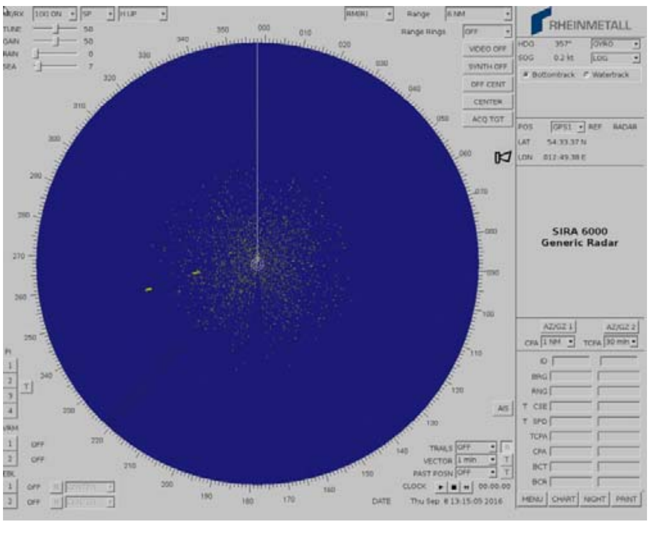


Figure 2. Snapshot of radar response to simulated multi-target scenario, showing both tug vessels clearly on screen.

The range was set to 6 NM at head-up display. Some sea clutter due to the simulated waves is visible.

3.1 *Target dynamics and measurement model*

In general, for tracking vessels of various types, we assume to propagate the state vector x_{k-1}^{t} of the t^{th} target to the next time frame k through a non-linear motion model following the notation of

$$\mathbf{x}_{k|k-1}^{t} = f^{i}\left(\mathbf{x}_{k-1}^{t}, \boldsymbol{\varepsilon}_{k}^{q}\right) \tag{1}$$

where $\boldsymbol{\varepsilon}_{k}^{q} \sim N\left(\mathbf{0}, \sum = \mathbf{Q}_{k}^{i}\right)$ and no further control input given. To distinguish between different dynamic models in the upcoming section, we introduce the superscript i to the non-linear function $f^{i}(\cdot)$. The predicted state estimate $\mathbf{x}_{k|k-1}^{t}$ will be corrected by evaluating the residual between the actual radar measurement $\mathbf{z}_{k}$ associated to the t^{th} target and the predicted measurement following the general formulation of

$$\hat{\mathbf{z}}_{k|k-1} = h\left(\mathbf{x}_{k|k-1}^{t}, \boldsymbol{\varepsilon}_{k}^{r}\right), \tag{2}$$

where $\boldsymbol{\varepsilon}_{k}^{r}$ is drawn from the assumed sensor noise distribution (e.g., $\boldsymbol{\varepsilon}_{k}^{r} \sim N\left(\mathbf{0}, \sum = \mathbf{R}_{k}\right)$ for the Gaussian assumption).

3.2 *The IMM-JPDA filter*

Considering the inherent trade-off between complexity and tracking performance the JPDA framework was chosen, being combined with an IMM filter to capture different target dynamics. In the remainder of this section, we will define the set of dynamic and measurement models that constitute the IMM-JPDA framework for multi-sensor, multi-target tracking. Being first introduced in Fortmann, Bar-Shalom, and Scheffe (1983), the key feature of the JPDA is the computation of conditional probabilities of joint association events

$$A(k) = \bigcap_{j=1}^{M} A_{jt}(k), \tag{3}$$

with respect to the current time k, in which $A_{jt}(k)$ represents the event of the j^{th} measurement originating from target t, with $1 \le j \le M$ and $0 \le t \le N$. In this context, M refers to the number of measurements at time k, N to the number of known targets and t_j is the target index the j^{th} measurement is associated to. With $t = 0$ the specific case of a measurement originating from clutter is also being considered. This means, in contrast to a Nearest Neighbor (NN) association rule, the JPDA also accounts for situations in which a single measurement can be assigned, with a certain likelihood, to multiple targets at the same time. Details can be found in Fortmann Bar-Shalom, and Scheffe (1983) and Bar-Shalom, Daum, and Huang (2009).

In this work, we use an extension to classical JPDA filtering known as IMM-JPDA filter. The IMM was introduced by Blom and Bar-Shalom (1988) to adapt to quickly changing target dynamics by considering a finite set of kinematic models that run in parallel. In contrast to hard switching schemes, the IMM weighs the different target state estimates based on the likelihood of each model to explain the current measurement data. The mode transition is thereby governed by an underlying Markov chain. In our case, we consider a set of two dynamic models to capture either straight path or turning maneuver based motion. For the former a Constant Velocity (CV) model was designed, whereas the Constant Turn Rate Velocity (CTRV) model is supposed to fit best to the latter. The corresponding target state vectors are defined as

$$\mathbf{x}_{k}^{CV} = \left[p_{e,k}, p_{n,k}, \psi_{k}, v_{k}\right]^{T}, \tag{4}$$

$$\mathbf{x}_{k}^{CTRV} = \left[p_{e,k}, p_{n,k}, \psi_{k}, v_{k}, \dot{\psi}_{k}\right]^{T}, \tag{5}$$

with $\{p_{e,k}, p_{n,k}\}$ the 2D position coordinates in the local ENU frame, ψ_{k} the course over ground, v_{k} the speed over ground and $\dot{\psi}_{k}$ the turn rate at time k. The uncertainty within the models is expressed in

$$\mathbf{Q}_{k}^{CV} = \begin{bmatrix} \sigma_{\psi}^{2} & 0 \\ 0 & \sigma_{v}^{2} \end{bmatrix}, \qquad \mathbf{Q}_{k}^{CTRV} = \begin{bmatrix} \sigma_{v}^{2} & 0 \\ 0 & \sigma_{\dot{\psi}}^{2} \end{bmatrix}. \tag{6}$$

The detailed definitions of the process models $f^{i}(\cdot)$ for CV and CTRV can be found in Siegert, Banyś, Martínez, and Heymann (2016). Careful attention needs to be paid to the augmentation of state vectors of different dimensions. In this paper we follow a strategy described in Glass, Blair, and Bar-Shalom (2013) for unbiased mixing of different process models. In contrast to the common formulation of either IMM or JPDA, which both use Extended Kalman Filtering (EKF) to adapt to non-linearities in the dynamic models, we deploy the Unscented Kalman Filter (UKF) instead (see Julier and Uhlmann, 1997). It turns out that due to the sigma point sampling approach the UKF is more robust against non-linearities induced by the radar measurement update equation, whereas the approximation to a first-order Taylor series expansion within the EKF was found to diminish its performance (see Braca, Vespe, Maresca, and Hoffmann (2012) for discussion). The combination of IMM and JPDA filtering schemes to a well-defined framework was initially proposed by Blom and Bar-Shalom (1988) and extended to the multi-sensor case in Tugnait (2003). In the end, a recursive step-by-step algorithm was derived fusing the asynchronous measurements from different sensors sequentially.

The final state update equation for the t^{th} target tracked in mode $i \in$ {CV, CTRV} becomes

$$\mathbf{x}_{k|k}^{t,i} = \beta_{0t}^{i} \mathbf{x}_{k|k-1}^{t,i} + \sum_{j=1}^{M_{t,k}} \mathbf{x}_{k|k}^{t,i}\left(j\right)\beta_{jt}^{i} , \tag{7}$$

with $M_{t,k}$ the number of validated measurements for target t and $\mathbf{x}_{k|k}^{t,i}\left(j\right)$ the UKF target estimate conditioned on the j^{th} measurement at time k. The weights β_{jt}^{i} are interpreted as association probabilities following the convention in Braca, Vespe, Maresca, and Hoffmann (2012), with

$$\begin{aligned} \beta_{0t}^{i} &= P\left\{ none\ of\ the\ measurements\ origins\ from\ target\ t \right\} \\ \beta_{jt}^{i} &= P\left\{ the\ j^{th}\ measurements\ origins\ from\ target\ t \right\} \end{aligned} \tag{8}$$

3.2.1 *Track management*

In general, the JPDA filter is subject to several assumptions. Most importantly for our application, the finite set of targets to be tracked is assumed to be known, i.e., neither track initialization nor track pruning is covered by the standard formulation of JPDA. To overcome these restrictions it is suggested in Bar-Shalom and Li (1995) to apply an *M*-of-*N* rule, which is implemented according to Braca, Vespe, Maresca, and Hoffmann (2012) as follows:

1. Track initialization:
   - For each radar scan, every unassigned target candidate measurement becomes a tentative track. The gate assigned to this track accounts for the (assumed) maximum velocity and sensor uncertainty, i.e., this bound is rather conservative.
   - If a target candidate from the next radar scan falls within the gate of a tentative track, it becomes a preliminary track. In case a tentative track is not supported by any detection in the next time frame it is dropped again.
   - For each preliminary track a UKF is initialized propagating the target state through a CV dynamic model.
   - If a preliminary track is confirmed for M out of the next N radar scans, it becomes a confirmed track. If not, it is dropped.
   - Each confirmed track will be tracked in the IMM-JPDA filter.
2. Track termination:
   - In case a confirmed track was not updated for Mt out of Nt consecutive radar scans it is terminated, where index t denotes a difference between M and N from the initialization process.
   - A confirmed track will also be terminated, in case the corresponding error state covariance exceeds thresholds in position and/or velocity.

3.2.2 *Target candidate extraction from radar images*

In order to update the IMM-JPDA filter with measurements, target candidates need to be detected and extracted from radar first. The utilized approach to extract radar target information is based on image processing instead of directly working on the radar signal level. To extract target candidates from the current radar image at time *k*, the following procedure is applied:

1. Masking the image to eliminate features of the user interface, e.g., colored heading lines, blob in center, radar information tables.
2. Conversion of the image from RGB to gray-scale (weighted average from color channels).
3. Blob detection with fixed range settings for convexity, circularity, inertia, size and intensity of expected targets.
4. Each detected target candidate per frame is expressed in range and bearing, relative to the position of the vessel carrying the radar.

The key aspect in this processing chain is certainly the scale-invariant blob detection to eventually detect target candidates. This algorithm is well-described in the literature and finds many applications in image based target detection and tracking such as described in Isard and MacCormick (2001). For this work the implementation provided by the OpenCV framework was used (OpenCV 3.1.0: https://github.com/Itseez/opencv.git). Figure 3 shows the final outcome of the different radar processing stages. The set of extracted radar measurements is defined as $\mathcal{Z}_k = \left\{ \mathbf{z}_k^1, \ldots, \mathbf{z}_k^M \right\}$ with the j^{th} measurement vector $\mathbf{z}_k^j = \left[z_k^r, z_k^b \right]^T$ comprising range and bearing of the target candidate. The state update of $\mathbf{x}_{k|k-1}^{i}$ conditioned on the associated radar target measurements is based on the definition of $h\left(\mathbf{x}_{k|k-1}^{i}, \boldsymbol{\varepsilon}_k^{r,s}\right)$ from Equation 2 given as

$$h\left(\mathbf{x}_{k|k-1}^{i}, \boldsymbol{\varepsilon}_k^{r,s}\right) = \begin{bmatrix} \sqrt{\left(p_{e,k|k-1} - p_e\right)^2 + \left(p_{n,k|k-1} - p_n\right)^2} \\ \arctan\left(\dfrac{p_{n,k|k-1} - p_n}{p_{e,k|k-1} - p_e}\right) \end{bmatrix} + \boldsymbol{\varepsilon}_k^{r} , \tag{9}$$

with $\{p_e, p_n\}$ the 2D reference coordinates of the radar system in the ENU frame of the tracked vessel.

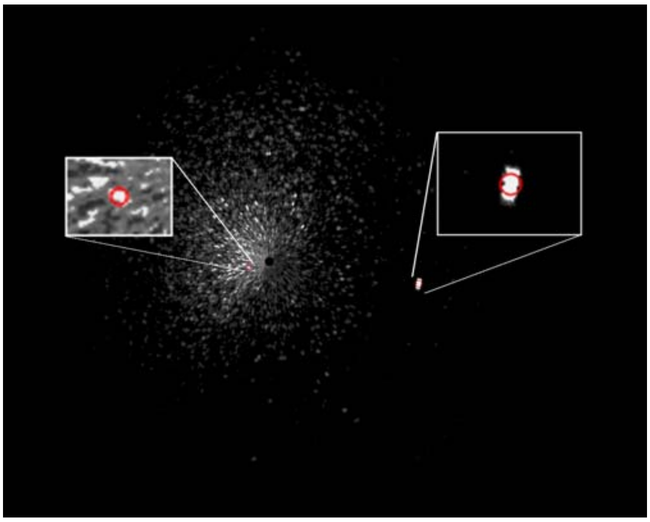


Figure 3. Extracted target candidates (red circles) at time k after blob detection in pre-processed radar image.

3.3 *The Repulsive Multi Particle Filter*

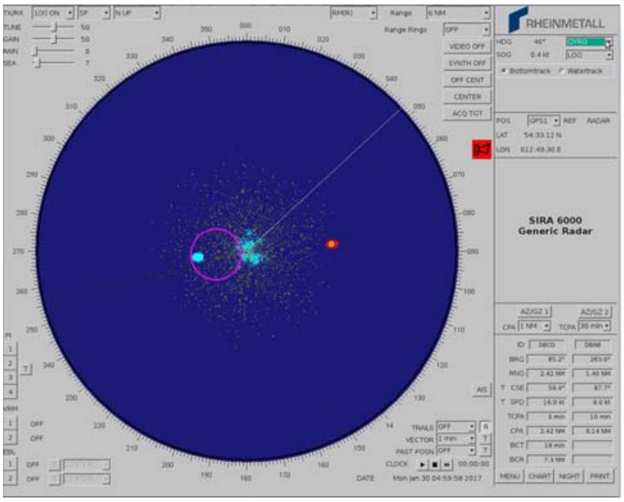
The use of particle filters in marine radar image processing (Heymann, Banyś, and Saez, 2015) showed the potential to overcome the assumption of non-Gaussian noise when using radar images as measurement input. However, this study uses a classical particle filter algorithm without any comparison of the results to existing fusion technologies. In this study, we compare the performance of both classes of recursive Bayesian filters, namely the particle filter (RMPF) and Kalman filter based (IMM-JPDA) approaches, in a maritime multi-target scenario.

Following the description of the target dynamics and measurement model in Section 3.1 the implementation of the particle filter used in this study uses the dynamic model of constant velocity and therefore the definition of the particle state space as in Equation 4 is used. Under the assumption of a hidden Markov process and conditional independent observations $\{\mathbf{y}_k, k \in \mathbb{N}\}$, $\mathbf{y}_k \in \mathbb{R}^{n_y}$ the formulations of Doucet, Godsill, and Andrieu (2000) are used. The RMPF implements the Sequential Importance Resampling (SIR) approach in which the particles resampling is done after every measurement step. In the SIR each new particle state $\mathbf{x}_k$ is sampled from the distribution $p\left(\mathbf{x}_k \mid \mathbf{x}_k^i\right)$.

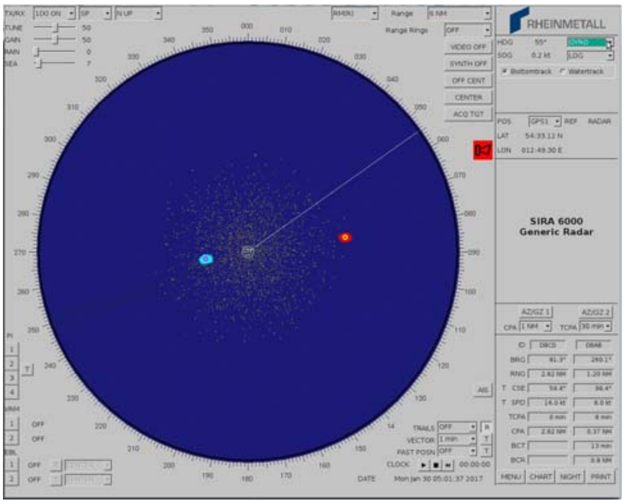
The RMPF was motivated by the classical behavior of sequential Monte Carlo trackers, which tend to converge to a single target solution. By exploiting this phenomenon together with the physical principle of repelling charged particles the main parts of the RMPF are described. As soon as the particle filter picks up the track of a single target, a new filter is initialized to start tracking a different target. The time to acquisition of a target is determined by a fixed threshold, which specifies a maximum uncertainty bound during target tracking. This particle filter generates a repellent force reducing the weight of the samples from other particle filters which are generated whenever a new target is detected. The down-weighting is defined by the following equation:

$$w(i) = \sum_j \exp\left(-3\left(\sigma_{\max}^i\right)^2\right), \tag{10}$$

where $w(i)$ is the weight of particle i in filter k, j is the loop variable over all other filters except k and $\sigma_{\max}^i$ is the largest standard deviation in the position domain.



(a) Acquisition phase of the 2nd target.



(b) Both targets are tracked by the RMPF.

Figure 4. Different stages of target acquisition for the Repulsive Multi Particle Filter.

The process of acquisition of the targets is illustrated in Figures 4a and 4b. The red points show the first particle filter which is fully converged in Figure 4a and the second filter is initialized and drawn to the target in the left part of the radar screen. This can be seen by the purple circle whose center position is at the mean of the particle distribution of the second filter and radius of the circle is determined by the largest standard deviation of the position domain. In Figure 4b the second filter has converged as well and both targets are finally tracked.

3.4 *MTT performance assessment*

In Schuhmacher, Vo, and Vo (2008) the Optimal Subpattern Assignment (OSPA) metric was introduced and is considered as state-of-the-art method for MTT performance assessment. The OSPA metric yields several characteristics that make it attractive for MTT performance assessment:

- It has a physical interpretation.
- It captures multi-target state errors and cardinality errors meaningfully.
  - The OSPA metric depends on only two tuning parameters (the order p and cut-off parameter c).
- It is relatively easy to compute.

Consider two finite subsets $X = \{x_1, \ldots, x_m\}$ and $Y = \{y_1, \ldots, y_n\}$ within W, where $m, n \in \mathbb{N}_0$, and denote by $\prod_k$ the set of permutations on $\{1, 2, \ldots, k\}$ for any $k \in \mathbb{N}$. The OSPA metric is then defined as the function

$$\bar{d}_p^{(c)}(X,Y) := \left(\frac{1}{n} \left(\min_{\pi \in \Pi_n} \sum_{i=1}^{m} d^{(c)}\left(x_i, y_{\pi(i)}\right)^p + c^p (n-m) \right) \right)^{\left(1/p\right)}, \quad (11)$$

with $d^{(c)}(x_i, y_{\pi(i)}) = \min(c, d(x,y))$ denoting the distance between x and y being cut off at $c > 0$. This definition holds for $m \leq n$, in case of $m > n$ we substitute $\bar{d}_p^{(c)}(X,Y)$ with $\bar{d}_p^{(c)}(Y,X)$. According to Schuhmacher, Vo, and Vo (2008), the impact of *localization* and *cardinality* errors to the overall metric can be expressed as

$$\bar{e}_{p,loc}^{(c)}(X,Y) := \left(\frac{1}{n} \min_{\pi \in \Pi_n} \sum_{i=1}^{m} d^{(c)}\left(x_i, y_{\pi(i)}\right)^p \right)^{\left(1/p\right)} \quad (12)$$

and

$$\bar{e}_{p,card}^{(c)}(X,Y) := \left(\frac{c^p (n-m)}{n} \right)^{\left(1/p\right)}. \quad (13)$$

4 RESULTS

We will evaluate both proposed multi-target trackers based on simulated radar images in the following section. In Figure 5 the resulting tracks of the IMM-JPDA are plotted on top of the extracted radar target candidates obtained from the blob detector. The corresponding output of RMPF is plotted in Figure 6. In this case only the estimated tracks are shown, since the filter is conditioned on the radar image not on a finite set of target candidates.

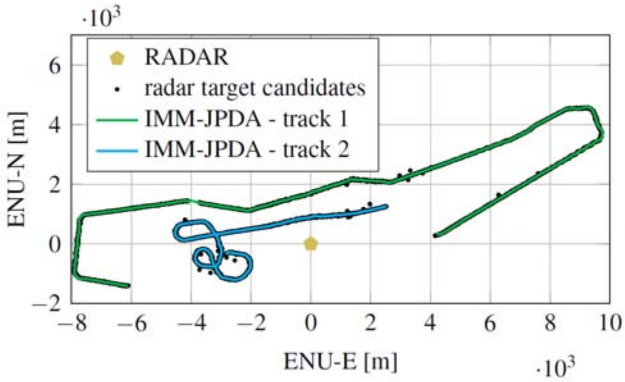


Figure 5. Resulting tracks (in blue and green) by applying the IMM-JPDA filter to the simulated multi-target scenario. The accumulated radar target candidates are plotted as black dots.

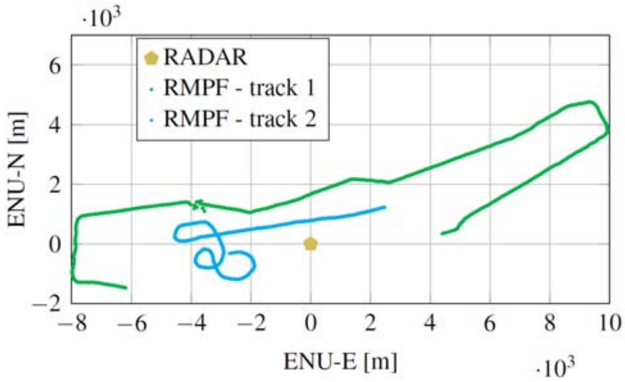


Figure 6. Resulting tracks (in blue and green) from applying the RMPF to the simulated multi-target scenario. Track 1 gets lost while the target moves in a blind spot of the radar. The filter converges back to the center of the image, as the clutter response is strongest close to the radar's position.

It can be observed that both filters pick up two tracks from the radar image data. The IMM-JPDA and RMPF are continuously tracking both vessels over the time of the simulation. The RMPF shortly loses one target at the point in time when the vessel is covered by the second ship in the radar. While IMM-JPDA filtering overpasses this outage of measurement updates by inflating the error state covariance due to continuous predictions the particles of the RMPF start to spread and acquire the remaining clutter response in the vicinity of the hidden target. At the time the vessel appears again in the radar image the filter converges quickly back to the correct position.

The OSPA metric to compare the two filters is shown in Figure 7. The overall OSPA metrics computed from Eq. 11 are plotted against time for both filters. In this analysis the cut-off parameter (penalizing cardinality errors) was set to c = 250 m; the order p to 2. In fact the short loss of one target in case of the RMPF is reflected only by small peaks compared to the performance of the IMM-JPDA. This is due to the chosen cut-off parameter c. If this parameter is set to 500 m the mismatch between the number of reference targets to the number of tracked objects gets a higher impact in the multi-target state error $\bar{d}_p^{(c)}(X,Y)$. Figure 8 shows the resulting graphs and the peak at around 2700s shows the higher impact of the multi target state error. However, in terms of the overall multi-target tracking accuracy both filters show similar performance, with the RMPF outperforming the IMM-JPDA at certain times.

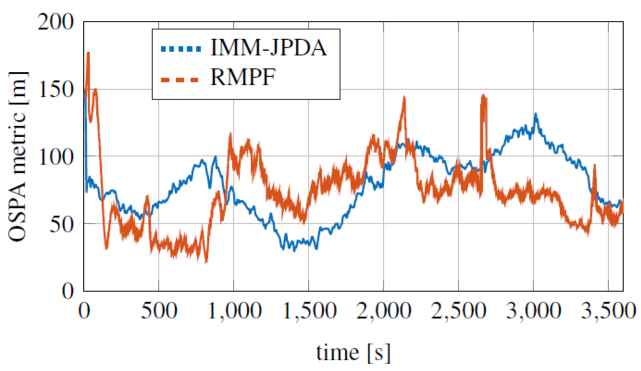


Figure 7. Performance comparison between the IMM-JPDA (dotted blue curve) and the Particle Filter (dashed red curve) on behalf of the OSPA metric, with c = 250 m and p = 2. The plot depicts the overall multi-target state errors $\bar{d}_p^{(c)}(X,Y)$.

Other parameters of interest for performance comparison are the *time-to-acquisition* and *completeness*. While the former describes the elapsed time until all tracks are picked up and confirmed, the latter denotes the ratio between the amount of correct multi-target states against the overall number of multi-target states. In Table 1 the corresponding values for each of the filters are listed. The numbers show that the IMM-JPDA framework is much faster in target acquisition, while the RMPF shows similar performance in terms of completeness.

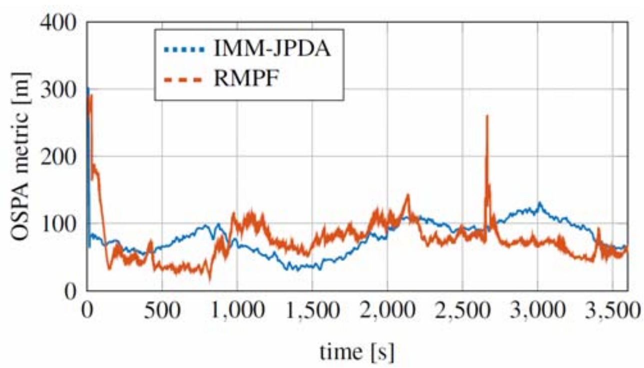


Figure 8. Performance comparison between the IMMJPDA (dotted blue curve) and the Particle Filter (dashed red curve) for c = 500 m and p = 2.

Table 1. Comparison between both multi-target trackers in terms of time-to-acquisition and completeness of multi-target state.

	Time-to-Acquisition	Completeness
IMM-JPDA	12 s	99.7 %
RMPF	31.6 s	97.4 %

5 CONCLUSION

In this paper we have compared two methods for maritime traffic situation assessment based on radar image processing. At first, an IMM-JPDA filter was designed that is conditioned on radar target candidates, which are extracted via blob detection from the current radar image. Secondly, a Repulsive Multi Particle Filter was proposed that uses the radar image directly as measurement input to update the particle distribution. In both cases, the track management, e.g., the target initialization, was done fully automatic. For performance evaluation we considered the multi-target state errors as well as time-to-acquisition and track completeness. It was shown that the RMPF and the IMM-JPDA are on par in all of those aspects. The accuracy of the multi-target state estimation is degraded in case of the RMPF after the loss of one target during times of coverage. This also affects the performance in terms of track completeness of the RMPF, which is slightly worse compared to the IMM-JPDA. Additionally, the RMPF takes more time to converge to a single target state, degrading its score on track completeness. However, in times of correct target acquisition the RMPF performs as good as the IMM-JPDA if not better.

REFERENCES

Bar-Shalom, Y., Daum, F., & Huang, J. (2009, December). The Probabilistic Data Association Filter. IEEE Control Systems Magazine.

Bar-Shalom, Y., & Li, X.-R. (1995). Multitarget-Multisensor Tracking: Principles and Techniques.

Blom, H. A. P., & Bar-Shalom, Y. (1988). The Interacting Multiple Model Algorithm for Systems with Markovian Switching Coefficients. IEEE Transactions on Automatic Control, 33.

Braca, P., Vespe, M., Maresca, S., & Horstmann, J. (2012). A Novel Approach to High Frequency Radar Ship Tracking Exploiting Aspect Diversity. Geoscience and Remote Sensing Symposium (IGARSS), 2012 IEEE International, 6895-6898.

Doucet, A., Godsill, S., & Andrieu, C. (2000, July). On sequential monte carlo sampling methods for bayesian filtering. Statistics and Computing, 10(3), 197–208. Retrieved from http://dx.doi.org/10.1023/A:1008935410038 doi: 10.1023/A:1008935410038

Doucet, A., Smith, A., de Freitas, N., & Gordon, N. (2001). Sequential Monte Carlo methods in practice. Springer New York. Retrieved from https://books.google.de/books?id=uxX-koqKtMMC

Fortmann, T., Bar-Shalom, Y., & Scheffe, M. (1983, Jul). Sonar tracking of multiple targets using joint probabilistic data association. IEEE Journal of Oceanic Engineering, 8(3), 173184. doi: 10.1109/JOE.1983.1145560

Glass, J. D., Blair, W. D., & Bar-Shalom, Y. (2013). IMM Estimators with Unbiased Mixing for Tracking Targets Performing Coordinated Turns. Proceedings IEEE Aerospace Conference.

Gordon, N., Salmond, D., & Smith, A. (1993, April). Novel approach to nonlinear/non-gaussian bayesian state estimation. IEE Proceedings F (Radar and Signal Processing), 140, 107113(6).

Guerriero, M., Willett, P., Coraluppi, S., & Carthel, C. (2008). Radar/AIS Data Fusion and SAR tasking for Maritime Surveillance. In International Conference on Information Fusion (Vol. 11th).

Heymann F., Banyś P., Sáez-Martínez C. (2015). Radar Image Processing and AIS Target Fusion. TransNav, the International Journal on Marine Navigation and Safety of Sea Transportation, Vol. 9, No. 3, pp. 443-448.

Hue, C., & Le Cadre, J.-P., & Pérez, P. (2002, July). Tracking multiple objects with particle filtering. IEEE

Transactions on Aerospace and Electronic Systems, 38(3).
Isard, M., & Blake, A. (1998, August). Condensation conditional density propagation for visual tracking. In (Vol. 28, p. 5-28).
Isard, M., & MacCormick, J. (2001). BraMBLe: A Bayesian multiple-blob tracker. In Eighth IEEE International Conference on Computer Vision (Vol. 2, p. 34-41).
Julier, S. J., & Uhlmann, J. K. (1997). A New Extension of the Kalman Filter to Nonlinear Systems. In Proc. of AeroSense: The 11th Int. Symp. on Aerospace/Defence Sensing, Simulation and Controls. (pp. 182–193).
Kazimierski, W., & Stateczny, A. (2015). Radar and Automatic Identification System Track Fusion in an Electronic Chart Display and Information System. The Journal of Navigation(68), 1141-1154.
Khaleghi, B., Khamis, A., Karray, F. O., & Razavi, S. N. (2013). Multisensor data fusion: A review of the state-of-the-art. Information Fusion, 14(1), 28 44. doi: http://dx.doi.org/ 10.1016/j.inffus.2011.08.001
Kim, C., Li, F., Ciptadi, A., & Rehg, J. M. (2015, Dec). Multiple hypothesis tracking revisited. In 2015 IEEE International Conference on Computer Vision (ICCV) (p. 4696-4704). doi: 10.1109/ICCV.2015.533
Kitagawa, G. (1996). Monte carlo filter and smoother for nongaussian nonlinear state space models. Journal of Computational and Graphical Statistics, 5(1), 1-25.
Mahler, R. (2015, Oct). A brief survey of advances in randomset fusion. In Control, automation and information sciences (iccais), 2015 international conference on (p. 62-67). doi: 10.1109/ICCAIS.2015.7338726
Mazzarella, F., & Vespe, M. (2015, April). SAR Ship Detection and Self-Reporting Data Fusion Based on Traffic Knowledge. IEEE Geoscience and Remote Sensing Letters.
Perera, L. P., Ferrari, V., Santos, F. P., Hinostroza, M. A., & Soares, C. G. (2015, APRIL). Experimental Evaluations on Ship Autonomous Navigation and Collision Avoidance by Intelligent Guidance. IEEE Journal of Oceanic Engineering, 40.
Pulford, G. W. (2005, October). Taxonomy of multiple target tracking methods. IEEE Proceedings Radar, Sonar and Navigation, 152(5), 291-304. doi: 10.1049/ip-rsn:20045064
Schuhmacher, D., Vo, B. T., & Vo, B. N. (2008, June). On performance evaluation of multi-object filters. In Information fusion, 2008 11th international conference on (p. 1-8).
Siegert, G., Banyś, P., & Heymann, F. (2016, July). Improving the Maritime Traffic Situation Assessment for a Single Target in a Multisensor Environment. In Maritime knowledge discovery and anomaly detection workshop proceedings (p. 7882). Ispra, Italy: European Commission Joint Research Center. doi: 10.2788/025881
Siegert, G., Banyś, P., Hoth, J., & Heymann, F. (2017, February). Counteracting the Effects of GNSS Jamming in a Maritime Multi-Target Scenario by Fusing AIS with Radar Data. In ION International Technical Meeting. Monterrey, CA, USA: International Organization of Navigation.
Siegert, G., Banyś, P., Martínez, C. S., & Heymann, F. (2016, April). EKF Based Trajectory Tracking and Integrity Monitoring of AIS Data. In IEEE/ION Position, Location and Navigation Symposium PLANS (p. 887 897). Savannah, GA: IEEE.
Tugnait, J. K. (2003, June). Tracking of multiple maneuvering targets in clutter using multiple sensors, imm and jpda coupled filtering. In American control conference, 2003. proceedings of the 2003 (Vol. 2, p. 1248-1253). doi: 10.1109/ ACC.2003.1239759